

**THE IMPACT OF NORMALIZATION TECHNIQUES ON
PERFORMANCE BACKPROPAGATION NETWORKS**

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**UNIVERSITI UTARA MALAYSIA
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ON PERFORMANCE BACKPROPAGATION
NETWORKS**

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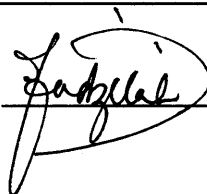
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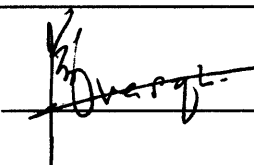
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ABSTRACT (BAHASA MELAYU)

Rangkaian neural (NN) adalah merupakan suatu model perkomputeran yang mempunyai keupayaan untuk belajar, pengitlakkan, dan model yang lazim digunakan ialah perseptron berlapis (MLP). Pembangunan NN yang baik bergantung kepada beberapa aspek seperti proses perolehan, pembentukan model, dan pemilihan model yang sesuai. Data perlu ditukarkan dalam bentuk yang boleh diterima pakai sebagai input kepada rangkaian M.I.P. Data yang telah melalui proses transformasi biasanya lebih berkesan dan mungkin mampu menghasilkan keputusan yang lebih tepat daripada rangkaian. Kajian yang dijalankan merangkumi beberapa jenis teknik normalisasi dengan penggunaan pembelajaran rambatan balik. Teknik normalisasi yang digunakan dalam eksperimen ialah teknik *Min-Max*, *Z-Score*, *Decimal Scaling*, *Sigmoidal* dan *Softmax* atau *Logistic*. Untuk mengkaji kesan teknik normalisasi terhadap prestasi NN, set data perubahan dengan nilai target Boolean dipraproses, dilatih, diukur kesahihan, dan pengujian menggunakan algoritma pembelajaran rambatan balik. Kriteria pemilihan model yang terbaik adalah berdasarkan peratus ramalan benar yang tertinggi. Tiga set data dan lima teknik normalisasi telah dilaksanakan pada fasa praproses data didalam proses pembangunan model NN. Keputusan bagi setiap teknik telah dikaji dan dipersembahkan, kemudian dibandingkan dengan pendekatan statistik. Keputusan menunjukkan bahawa penggunaan teknik normalisasi yang berbeza menghasilkan prestasi yang berbeza. Kajian ini juga mendapati bahawa kelima-lima teknik normalisasi yang dikaji keatas pendekatan statistik (*Logistic regression*) menunjukkan peratus ramalan benar yang rendah berbanding dengan pendekatan NN. Dapatan kajian ini tidak hanya menyumbang kepada peningkatan prestasi algoritma pembelajaran rangkaian rambatan balik tetapi juga dapat membantu didalam membuat keputusan bagi pemilihan teknik normalisasi yang sesuai bagi data tertentu.

ABSTRACT (ENGLISH)

Neural networks (NN) are computational models with the capacity to learn, generalize, and the most used are multi-layer perceptrons (MLP). Building successful NN applications depends on several aspects such as the process of acquiring, modeling and selecting the appropriate model. The data needs to be transformed into a form that is acceptable as input to the MLP network. The transform data often determines the efficiency and possibly the accuracy of results from the network. This study explored several normalization techniques using backpropagation learning. The normalization techniques used in the experiments are Min-Max, Z-Score, Decimal Scaling, Sigmoidal, and Softmax or Logistic techniques. To explore the impact of normalization techniques on the performance on NN, medical datasets with Boolean target were preprocessed, trained, validated and tested using backpropagation learning algorithm. The criterion of choosing the best model is based on the highest percentage of correct prediction. Three datasets and five normalization techniques were employed in the data preprocessing phase of building the NN models. The results of each normalization techniques are presented and compared with statistical approach. The results reveal that the utilization of different normalization techniques produces different NN performance. The experiments also indicate that all five normalization techniques of logistic regression achieve lower percentage of correct prediction than the results produced using NN. The findings will not only contribute towards enhancing the performance of backpropagation nets but it will also assist in making decision to the choice of normalization techniques to be applied to a particular dataset.

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CHAPTER 1

INTRODUCTION

In this chapter, the first section describes the context of the study that presents an introduction to data preparation in Neural Network (NN), followed by the problem statement, the objectives of the study and the significance of the study. Finally, the scope of the study that includes the limitations of the study is also discussed.

1.1 Preprocessing

Data in the real world are often dynamic, incomplete which are lacking attribute values, lacking certain attributes of interest, or containing only aggregate data, containing errors or outliers that is known as noisy data (Han and Kamber, 2001). It also an inconsistent which are containing discrepancies in codes or names, and most of the problem which appear in the data mining step within the knowledge discovery process are due to an inadequate preprocessing of the data present in these databases (Gomez-Skarmeta, 1997).

Before applying any of the built-in functions for training, it is important to check that the data is *reasonable* (Wolfram, 2003). Naturally, it cannot expect to obtain good models from poor or insufficient data. Unfortunately, there is no standard procedure that can be used to test the quality of the data. Even if they appear to be quite reasonable, it might be a good idea to consider preprocessing the data before initiating training. Preprocessing is a transformation, or conditioning, of data designed to make modeling easier and more robust (Wolfram, 2003). For example, a known nonlinearity in some given data could be removed by an appropriate transformation, producing data that conforms to a linear model that is easier to work with.

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